An Automatic Finite-Sample Robustness Metric: Can Dropping a Little Data Make a Big Difference?

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Dropping data: Motivation

More data & cheaper computation $\Rightarrow$
Statistical analyses are playing larger roles in decision making.

Decisions are important: We want **trustworthy** conclusions.
Data / models not always perfect: We want **robust** conclusions.

Would you be concerned if you could **reverse your conclusion** by removing a **small proportion** (say, 0.1%) of your data?

Running example: Angelucci et al. [2015], a randomized controlled trial study of the efficacy of microcredit based on 16,560 data points.
We can reverse the studies qualitative conclusions by removing 15 observations ($< 0.1\%$ of the data).

How do we find sets of influential points? Difficult in general!

We provide a **automatic approximation** with finite-sample guarantees.

The approximation gives the **causes of sensitivity** to data dropping.

Dropping data: Mexico Microcredit

Consider Angelucci et al. [2015], a randomized controlled trial study of the efficacy of microcredit in Mexico based on 16,560 data points. The variable "Beta" estimates the effect of microcredit in US dollars.

	Beta (SE)
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Original conclusion:
There is no evidence that microcredit is effective.

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The culprit is signal to noise ratio.
By the end of the talk, we will see that the sensitivity is due to

- High variability of the outcome (hosehold profit) relative to
- A small signal driving the conclusion (statistical significance)

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Would you be concerned if you could **reverse your conclusion** by removing a **small proportion** (say, 0.1%) of your data?

Not always! But sometimes, surely yes.

Thinking without random noise can be helpful.

Suppose you have a farm, and want to know whether your average yield is greater than 170 bushels per acre. At harvest, you measure 200 bushels per acre.

- Scenario one: If your yield is greater than 170 bushels per acre, you make a profit.
    - Don't care about sensitivity to small subsets
- Scenario two: You want to recommend your farming methods to a friend across the valley.
    - Might care about sensitivity to small subsets

For example, often in economics:

- Small fractions of data are missing not-at-random,
- Policy population is different from analyzed population,
- We report a convenient summary (e.g. mean) of a complex effect,
- Models are stylized proxies of reality.

Which estimators do we study?

Z-estimators. Suppose we have N data points $\vec{d} = d_1, \ldots, d_N$. Then:

$$\hat{\theta} := \vec{\theta} \text{ such that } \sum_{n=1}^{N} G(\vec{\theta}, d_n) = 0_P.$$

Examples: MLE, OLS, VB, &c (all minimizers of smooth empirical loss).

Function of interest. Qualitative decision based on $\phi(\hat{\theta}) \in \mathbb{R}$. E.g.:

- A particular component: $\phi(\theta) = \theta_d$
- The end of a confidence interval: $\phi(\theta) = \theta_d + \frac{1.96}{\sqrt{N}} \hat{\sigma}(\hat{\theta})$

Fix a proportion $0 < \alpha \ll 1$ of points to drop and find a set $\mathcal{S} \subset \{1, \ldots N\}$ with $|\mathcal{S}| \le \lfloor \alpha N \rfloor$ that extremizes $\phi(\hat{\theta})$ when dropped.

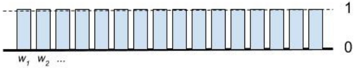
- **Problem:** There are many sets with $|\mathcal{S}| \le \lfloor \alpha N \rfloor$.
  - E.g., in Angelucci et al. [2015], $\binom{16{,}560}{15} \approx 1.5 \cdot 10^{51}$
- **Problem:** Evaluating $\phi(\hat{\theta}(\vec{d}_{-\mathcal{S}}))$ requires an estimation problem.
  - E.g., in Angelucci et al. [2015] computing the OLS estimator.
  - Other examples are even harder (VB, machine learning)

An approximation is needed!

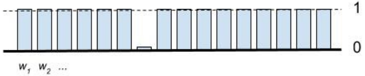
Which estimators do we study?

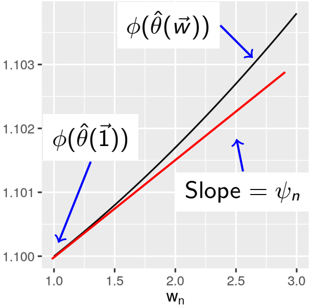
$$\hat{\theta} := \vec{\theta} \text{ such that } \sum_{n=1}^{N} G(\vec{\theta}, d_n) = 0_P.$$

Original weights: $\vec{1} = (1, \ldots, 1)$



Leave points out by setting their elements of $\vec{w}$ to zero.





The slopes $\psi_n := \left. \frac{\partial \phi(\hat{\theta}(\vec{w}))}{\partial \vec{w}_n} \right|_{\vec{1}}$ are values of the **empirical influence function** [Hampel, 1986]. We call them "influence scores."

Second-order derivatives control the error of the linear approximation.

Which estimators do we study?

$$\hat{\theta}(\color{red}{\vec{w}}) := \vec{\theta} \text{ such that } \sum_{n=1}^{N} \color{red}{\vec{w}_n} G(\vec{\theta}, d_n) = 0_P.$$

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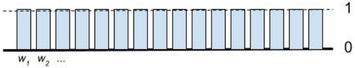

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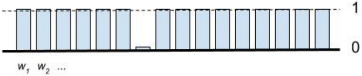

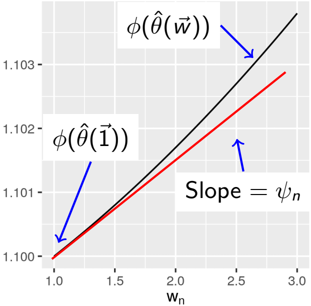

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Second-order derivatives control the error of the linear approximation.

Taylor series approximation.

Problem: How large can you make $\phi(\hat{\theta}(\vec{w}))$ leaving out no more than $\lfloor \alpha N \rfloor$ points? **Combinatorially hard!**

To simplify the search over $\vec{w}$, we form the Taylor series approximation:

$$\phi(\hat{\theta}(\vec{w})) \approx \phi^{\mathrm{lin}}(\vec{w}) := \phi(\hat{\theta}(\vec{1})) + \sum_{n=1}^{N} \psi_n (\vec{w}_n - 1)$$

Approximate solution: How large can you make $\phi^{\mathrm{lin}}(\vec{w})$ leaving out no more than $\lfloor \alpha N \rfloor$ points? **Easy!**

The most influential points for $\phi^{\mathrm{lin}}(\vec{w})$ have the most negative ψ_n.

The ψ_n are automatically computable using the **implicit function theorem** and **automatic differentiation**.

We provide **finite-sample theory** showing that
$\left|\phi(\hat{\theta}(\vec{w})) - \phi^{\mathrm{lin}}(\vec{w})\right| = O\left(\left\|\frac{1}{N}(\vec{w} - \vec{1})\right\|_2^2\right) = O(\alpha)$ as $\alpha \to 0$.

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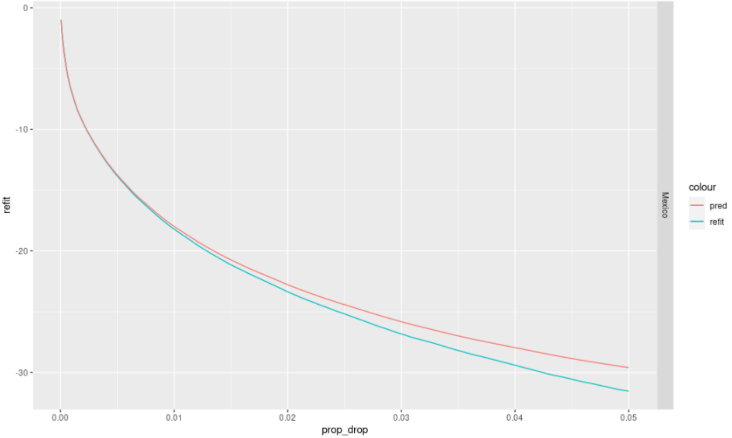
6. **Optional:** Compute $\hat{\theta}(\vec{w}^*)$, and verify that $\phi(\hat{\theta}(\vec{w}^*)) - \phi(\hat{\theta}) \ge \Delta$.

Mexico example:
See microcredit_profit_sandbox.R.



Selected experimental results.

Study case	Original estimate (SE)	Target change	Refit estimate	Observations dropped
Mexico	-4.549 (5.879)	Sign change	**0.398 (3.194)**	$1 = 0.01\%$
		Significance change	-**10.962 (5.565)***	$14 = 0.08\%$
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Poor, period 10	33.861 (4.468)*	Sign change	-**2.559 (3.541)**	697 = 6.63%
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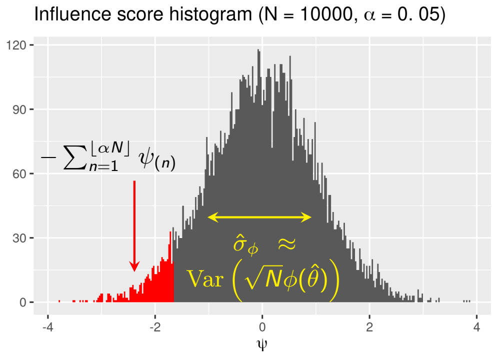
Health notpoor 12m	0.029 (0.005)*	Sign change	**-0.001 (0.005)**	156 = 0.67%
		Significance change	**0.008 (0.005)**	101 = 0.43%
		Significant sign change	**-0.009 (0.004)***	224 = 0.96%

Table: Medicaid profit results [Finkelstein et al., 2012]

What makes an estimator non-robust? A tail sum.

We show that $\phi^{\mathrm{lin}}(\vec{w}^*) - \phi(\hat{\theta}) = -\sum_{n=1}^{\lfloor \alpha N \rfloor} \psi_{(n)} =: \hat{\sigma}_\phi \hat{\mathscr{T}}_\alpha$ where

- The "noise" $\hat{\sigma}_\phi^2 \to \mathrm{Var}(\sqrt{N}\phi)$
  - $\hat{\sigma}_\phi^2 =$ is the robust "sandwich" variance estimator [Hampel, 1986]
- The "shape" $\hat{\mathscr{T}}_\alpha \le \sqrt{\alpha(1-\alpha)}$ determined by ψ_n distribution
  - $\hat{\mathscr{T}}_\alpha$ converges to a nonzero constant



Example.

Report non-robustness if:

$$\phi^{\text{lin}}(\vec{w}^*) - \phi(\hat{\theta}) = \hat{\sigma}_\phi \hat{\mathscr{T}}_\alpha \geq \Delta \qquad \Leftrightarrow \qquad \frac{\Delta}{\hat{\sigma}_\phi} \leq \hat{\mathscr{T}}_\alpha.$$

The **signal to noise ratio** $\frac{\Delta}{\hat{\sigma}_\phi}$ determines sensitivity to data dropping.

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Let's analyze with $\alpha = 0.01 = 1\%$.

$$\begin{array}{rlll}
\phi(\hat{\theta}) = & -0.029 & \text{(Increase QOI by defn)} & \\
\hat{\sigma}_\phi = & 0.766 & \text{(Noise)} & \\
\hat{\mathscr{T}}_\alpha = & 0.046 & \text{(Shape)} & \\
\hat{\mathscr{T}}_\alpha \hat{\sigma}_\phi = & 0.035 & \text{(Data dropping sensitivity)} &
\end{array}
\qquad
\begin{array}{rll}
\Delta = & 0.029 & \\
\frac{1}{\sqrt{N}}\hat{\sigma}_\phi = & 0.005 & \text{(SE)} \\
\frac{1.96}{\sqrt{N}} = & 0.0128 & \to 0 \text{ as } N \to \infty \\
\frac{1.96}{\sqrt{N}}\hat{\sigma}_\phi = & 0.010 & \text{(SE sensitivity)}
\end{array}$$

The noise is much larger than the signal $\Rightarrow$ Sensitive to data dropping.

Corollaries.

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Corollary: To robustify, reduce the noise or increase the signal.

Other forms of robustness

We proceeded as follows:

1. Took presence of datapoints as a model input,
2. Formed an automatically-computable differential approximation,
3. Provided theory by analyzing higher-order derivatives,
4. Studied its effectiveness in problems with open-access data.

Presence of datapoints is only one model input of many!

- Prior sensitivity in Bayesian nonparametrics [Giordano et al., 2021]
- Model sensitivity of MCMC output [Gustafson, 2000, Giordano et al., 2018]
- Cross-validation [Giordano et al., 2019, Wilson et al., 2020]
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- Frequentist variances of MCMC posteriors (in progress)

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- We can quickly and automatically find an approximate influential set which is accurate for small sets.
- Robustness to removing small sets is principally determined by the signal to noise ratio.
- In the present work, we studied data dropping. But we provide a framework for studying many other robustness questions, both to data and model perturbations.

Links and references

Tamara Broderick, Ryan Giordano, Rachael Meager (alphabetical authors)
"An Automatic Finite-Sample Robustness Metric: Can Dropping a Little Data Change Conclusions?"
https://arxiv.org/abs/2011.14999

Open-source software:

R package `zaminfluence`	`https://github.com/rgiordan/zaminfluence`
Python package `vittles`	`https://github.com/rgiordan/vittles`

Some related content can be found on my blog:
`https://rgiordan.github.io/`

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